Uncertainty in sea level rise projections due to the dependence between contributors

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Key Points:

- Most sea level projections include important assumptions about the dependence between contributors
- The uncertainty is underestimated with the independence assumption
- The uncertainty in the dependence structure is a major uncertainty that is always neglected in projections

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Abstract

Sea level rises at an accelerating pace threatening coastal communities all over the world. In this context sea level projections are key tools to help risk mitigation and adaptation. Projections are often made using models of the main contributors to sea level rise (e.g. thermal expansion, glaciers, ice sheets). To obtain the total sea level these contributions are added, therefore the uncertainty of total sea level depends on the correlation between the uncertainties of the contributors. This fact is important to understand the differences in the uncertainty of sea level projections from different methods. Using two process-based models to project sea level for the 21st century, we show how to model the correlation structure and its time dependence. In these models the correlation primarily arises from uncertainty of future global mean surface temperature that correlates with almost all contributors. Assuming that sea level contributors are independent of each other, an assumption made in many sea level projections, underestimates the uncertainty in sea level projections. As a result, high-end low probability events that are important for decision making are underestimated. The uncertainty in the strength of the dependence between contributors is also explored. New dependence relations between the uncertainty of dynamical processes, and surface mass balance in glaciers and ice sheets are introduced in our model. Total sea level uncertainty is found to be as sensitive to the dependence between contributors as to uncertainty in certain individual contributors like thermal expansion and Greenland ice sheet.

1 Introduction

Global sea level rise has accelerated in the 20th century compared to the late Holocene background rate [*Gehrels and Woodworth*, 2013; *Church et al.*, 2013; *Hay et al.*, 2015; *Kopp et al.*, 2016; *Dangendorf et al.*, 2017]. An acceleration has also been detected during the satellite altimetry period [*Chen et al.*, 2017; *Dieng et al.*, 2017; *Nerem et al.*, 2018]. This is mainly due to anthropogenic greenhouse gas emissions [*Slangen et al.*, 2016]. It is therefore crucial to make reliable projections of future sea level rise depending on future greenhouse gas emissions and to gain insights into their uncertainties to help society make the best mitigation and adaptation decisions [*Nicholls et al.*, 2014; *Hinkel et al.*, 2014; *Le Cozannet et al.*, 2017; *Nauels et al.*, 2017a].

One way to make future projections of complex systems like the earth's climate is to use numerical models that are based on a physical understanding of the relevant processes. Climate models or earth system models are used to project future temperature increase [*Collins et al.*, 2013]. Unfortunately these models do not yet include all of the important processes driving future sea level. Glaciers and ice caps are too small to be resolved by their coarse spatial resolution. Ice sheets are large enough but the main physical processes determining their response to climate change are still uncertain [*Church et al.*, 2013; *Deconto and Pollard*, 2016; *Pattyn et al.*, 2017]. Also their long time scale of adjustment and sensitivity to small circulation and temperature biases still make it challenging to include them in fully coupled models [*Vizcaíno et al.*, 2010; *Joughin et al.*, 2012; *Lenaerts et al.*, 2015].

Until now two methods have been used to circumvent this shortcoming [*Moore et al.*, 2013]. A semi-empirical relation can be found between sea level rise and global mean surface temperature or top of atmosphere radiative balance. It can then be used into the future using data from climate models as a forcing [*Rahmstorf*, 2007]. Because of an increased availability of data, the semi-empirical method can now also be used at the level of individual sea level contributors [*Mengel et al.*, 2016]. New approaches make use of simple mechanistically motivated models of sea level contributors together with statistical methods to perform extensive calibration with observations or complex models [*Bakker et al.*, 2017; *Wong et al.*, 2017; *Nauels et al.*, 2017b]. These approaches bridge the gap between the semi-empirical method and the process-based method that also tries to evaluate the magnitude of each sea level rise contributor individually but using the most detailed physics possible. In the process-based method numerical models of physical processes are used when they are reliable and other sources of information are used otherwise [*Meehl et al.*, 2007; *Church et al.*, 2013]. Typically thermal expansion comes from state of the art climate models, ice sheet surface mass balance comes from regional models or empirical relationship between increase precipitation and increase temperature, ice sheet dynamics comes from either ice sheet models, expert judgement or statistical projections, or from a combination of all of these.

For all these methods, once the probability distribution or some other uncertainty measure has been quantified for each contributor to sea level rise, they are combined to obtain the total future sea level rise and its uncertainty. Information about the dependence between the sea level contributors is necessary for that step [*Kurowicka and Cooke*, 2006; *Meehl et al.*, 2007; *Church et al.*, 2013]. How this dependence influences the projection of total sea level is the subject of this paper.

A change of the correlation structure in the sea level projections of the Intergovernmental Panel on Climate Change (IPCC) Assessment Report 4 (AR4) [*Meehl et al.*, 2007] compared to the Third Assessment Report [*Church et al.*, 2001] was the main reason for the reduction of the uncertainty. Still this subject has received little attention in the literature until now probably because the focus has mainly been on projecting the expected value or the *likely* range of probabilities (e.g. a range that has a probability of 66% or more, *Church et al.* [2013]), while the quantiles far away from the expected value are more sensitive to the dependence between contributors. Now the probability range of interest broadens because low probability events are also important for risk-management if they have a high impact [*Hinkel et al.*, 2015]. For example *Jevrejeva et al.* [2014], *Mengel et al.* [2016] and *Bakker et al.* [2017] go up to the 95th percentile, *Grinsted et al.* [2015], *Jackson and Jevrejeva* [2016] and *Le Bars et al.* [2017] up to the 99th percentile and *Kopp et al.* [2014] up to the 99.9th percentile. It is therefore time to look at the sensitivity of results from the process-based method to the dependence between contributors.

The study of dependence between sea level contributors is similar to the study of co-incidence of storm surge, tides and river discharge that can lead to coastal flooding. Mathematically the problem is the same but in practice it is easier to constrain the dependence between coastal processes because observational data and more complete physical models are available [*Van den Hurk et al.*, 2015; *Klerk et al.*, 2015]. This allows the use of bivariate statistics tools like copulas to investigate compounding effects [*Wahl et al.*, 2015; *Moftakhari et al.*, 2017]. The problem of dependence of sea level contributors is also more difficult to understand because it is not about events that correlate in time, for which we have a good intuition, but about events that correlate in the ensemble of possible futures that is a more abstract concept.

In section 2 we shortly review current practices to propagate the uncertainty from individual contributors to total sea level. The two sea level rise projection models that we use in this paper are then described in section 3 and their results are analysed in section 4. The paper finishes with a discussion and a conclusion.

2 Dependence between sea level contributors: the problem and a review of current practices

Mathematically sea level projections can be seen as a sum of random variables. The random variables, which are time dependent, are the contributors to sea level rise (e.g. thermal expansion, glaciers) and the total sea level rise is therefore a random variable. The expected value of the total sea level is the sum of the expected values of the contributors, and is therefore independent of the dependencies between the sea level contributors [*Beaumont*, 2005]. However, the distribution of the total sea level is sensitive to the dependencies. When two independent random variables are added, the variance of their sum is the sum of their variances, but for positive correlation the variance of the sum increases compared to the independent case and for negative correlation it decreases [*Beaumont*, 2005]. This result is obtained without any assumption on the probability distribution of the random variables and is key to understand the results described in section 4.

To compute the total sea level probability distribution it is therefore necessary to know the joint probability distribution formed by the sea level contributors. The probability distributions of each sea level contributor are then the marginal probability distributions of this joint probability distribution. This is a well known mathematical problem that has been widely discussed [*Kurowicka and Cooke*, 2006], but not yet in the context of sea level projections. A consequence is that the importance of the choice of dependencies between sea level contributors is not yet fully recognised in the literature.

We now give a short review of the different choices that have been made to project sea level in the literature. *Katsman et al.* [2011], *Slangen et al.* [2012] and *Jackson and Jevrejeva* [2016] assume independence between sea level contributors. For their global projections, *Kopp et al.* [2014] and *Kopp et al.* [2017] also make this assumption. On the other hand, *Horton et al.* [2015] assume correlation of 1 between all contributors. *Jevrejeva et al.* [2014] also use this assumption but only when computing an upper limit to future sea level rise. *Hinkel et al.* [2014] also assume complete dependence but only between land ice contributors.

Other studies mix independence and complete dependence depending on the contributors. To provide an uncertainty range to regional sea level rise projections, Assessment Report 5 (AR5) [*Church et al.*, 2013] assumed complete dependence between ocean steric/dynamical contribution and ice sheet SMB which are then independent of other contributors (see equation 13.SM.1 in *Church et al.* [2013]). This choice was based on the main origin of the uncertainty of the contributors. Similarly, *Slangen et al.* [2014] assume complete dependence between the two ice sheets SMB on the one hand and ice dynamics on the other hand. Then processes related to global climate models are completely dependent (ocean steric and dynamical effects, glaciers, ice sheet SMB) but are independent to ice sheet dynamics and land water.

A different method is used by *Meehl et al.* [2007] and *Church et al.* [2013] for the global process-based projections in which the Global Mean Surface Temperature (GMST) is used as a driver for some of the sea level contributors. This results in partial correlation between these contributors. The same approach was then used by *De Vries et al.* [2014] and by *Le Bars et al.* [2017] who extended the temperature sensitivity to the Antarctic dynamics contribution. An approximation of the correlation structure defined by *Church et al.* [2013] was used by *Jevrejeva et al.* [2014] and *Grinsted et al.* [2015] in which a joint probability distribution was built using constant correlation coefficients that emulate the results from *Church et al.* [2013] without modelling the time dependent dependence though temperature forcing.

Partial correlation between contributors due to a common dependence to GMST also arises in models that are directly constrained by observations or by more complex models. To define semi-empirical models for each major sea level contributor, *Mengel et al.* [2016] use pursuit curves driven by GMST. In the MAGICC sea level model [*Nauels et al.*, 2017a], that emulates complex climate models, GMST is also used to drive the ice sheets and glaciers models. The situation is similar for the simple mechanistically motivated model BRICK [*Wong et al.*, 2017; *Bakker et al.*, 2017] that uses a two-step calibration process where contributors are first calibrated individually and then the total sea level is also calibrated using total sea level observations. These approaches naturally extend dependence to GMST to the ice sheet dynamics which is not the case in *Church et al.* [2013]. Using GMST as a driver for all or some sea level contributors generally results in positive correlation between the uncertainty of contributors, except for Antarctic SMB that is expected to accumulate mass as temperature increases [*Gregory and Huybrechts*, 2006].

A different way to correlate uncertainty in sea level projections is to use an expert judgement assessment as in *Bamber and Aspinall* [2013] who found a correlation of 0.7 between the Greenland ice sheet and the West Antarctic ice sheet and -0.2 between the East Antarctic ice sheet and the other two ice sheets. This correlation structure was used by [*Kopp et al.*, 2014] for a sensitivity experiment showing that for the RCP8.5 scenario in 2100 the 99.5th percentile of their sea level projection increased from 176 cm in their default uncorrelated assumption to 187 cm. This shows the effect of the correlation structure for the tail of future sea level distribution.

3 Method

Two similar models are used to project total global sea level. The process-based method as presented in the AR5 [*Church et al.*, 2013] is used as a starting point. A probabilistic model is then constructed with a few modifications. The following method description builds on *Church et al.* [2013], *De Vries et al.* [2014] and *Le Bars et al.* [2017] with improved description of the dependence between contributors but less detailed description of the modelling of individual contributors. Dependence is measured using the Spearman (or rank) correlation. We use capital letters for random variables, bold capital letters for matrices and calligraphic letters for distributions.

3.1 AR5 process-based model

In this model the dependence between the sea level contributors is set indirectly through a common dependence to GMST [*Church et al.*, 2013]. Greenland SMB, glaciers and ice caps and Antarctic SMB are driven by GMST. Thermal expansion comes from climate models and is then assumed to be perfectly correlated to GMST. Antarctic dynamics has a small dependence on temperature because it depends on Antarctic SMB. More surface accumulation results in more mass loss through dynamical processes. Greenland dynamics is assumed independent of GMST. See Fig. 1 for a visual summary of the dependence structure.

3.1.1 Global mean surface temperature

The temperature fields are derived from the same 21 climate models that were used in IPCC AR5 *Church et al.* [2013]. They are part of the Coupled Model Intercomparison Project Phase 5 (CMIP5).

The number of models is not large enough to determine the shape of the underlying distribution of the time varying global mean surface temperature. Therefore, this distribution is assumed to be normal. The global annual mean surface temperature information from all models is represented by a matrix $\mathbf{T}$, whose first dimension is time (t), and second dimension are the member of the model ensemble. N_1 is a random variable following the normal distribution of mean 0 and standard deviation 1 ($\mathcal{N}(0,1)$). Then for each time t the random variable representing temperature (T) is computed from the mean temperature ($\bar{T}$) and standard deviation ($\sigma(T)$) over the climate model ensemble, as:

$$T(t) = \overline{\mathbf{T}}(t) + \gamma\sigma(\mathbf{T}(t,.))N_1, \quad (1)$$

where γ is a scaling of the uncertainty that is equal to 1 for this model but changes in the probabilistic model. The temperature is generally used as an anomaly compared to a reference period. In the following a reference temperature distribution computed with the reference period 1986-2005 will be written $T_{1986-2005}$.

3.1.2 Global steric expansion

Global mean steric expansion is computed from the climate models in the same way as *Church et al.* [2013]. From each model and at all time t global mean steric expansion is stored in a matrix $\mathbf{X}_{st}$. The distribution is computed in the same way as for GMST:

Global Glacier Model	f ($mm\,°C^{-1}\,yr^{-1}$)	p (no unit)
Giesen and Oerlemans [2013]	3.02	0.733
Marzeion et al. [2012]	4.96	0.685
Radić et al. [2014]	5.45	0.676
Slangen and Van De Wal [2011]	3.44	0.742

Table 1. Parameters for the fits to the global glacier models.

$$X_{st}(t) = \overline{\mathbf{X}}_{st}(t) + \gamma\sigma(\mathbf{X}_{st}(t,.))N_1. \tag{2}$$

The random variable N_1 here is the same as in equation 1 which means that temperature and steric expansion are assumed to be completely correlated. This is not the case in climate models as we discuss in section 3.2.3 so this assumption is modified in the probabilistic model.

3.1.3 Land glaciers and ice caps

This contribution is computed in the same way as *Church et al.* [2013], it excludes Antarctic glaciers that are included directly in the Antarctic contribution but includes Greenland glaciers. Four global glacier models are used [*Giesen and Oerlemans*, 2013; *Marzeion et al.*, 2012; *Radić et al.*, 2014; *Slangen and Van De Wal*, 2011]. We first need to fit the time series of cumulated contribution to $fI(t)^p$, with $I(t)$ the time integral of GMST from year 2006 to t. The integrated temperature needs to be used here because the cumulated sea level contribution depend on past temperatures. The fitting parameters f and p obtained for each model are shown in Table 1. This method allows to apply these four models for any temperature pathway. In particular for the RCP scenarios:

$$I(t) = \int_{2006}^{t} T_{1986-2005}\,dt', \tag{3}$$

$$X_{gic}(t) = x^0_{gic} + \frac{10}{4}N_2\sum_{i=1}^{4} f_i I(t)^{p_i} \tag{4}$$

where X_{gic} is a random variable representing the sea level change in cm and i is an index looping over the four sets of parameters from the glacier models. The factor 10 is used to convert from mm to cm. The spread of the four models estimates around the mean is about 20%. This uncertainty is included with the random variable N_2 that follows the distribution $\mathcal{N}(1, 0.2^2)$. The variable N_2 is independent from N_1 which means that glacier modelling uncertainties are not correlated with temperature. The random variable X_{gic} is still partially correlated with temperature because $T_{1986-2005}$ is used to compute I. An additional constant ($x^0_{gic} = 0.95\,\mathrm{cm}$) is added to include the change from 1996 to 2005.

3.1.4 Greenland Ice Sheet Surface Mass Balance

The following parameterization is used for the surface mass balance tendency ($\dot{X}_{Gsmb}$) in terms of global temperature change [*Fettweis et al.*, 2013]:

$$\dot{X}_{Gsmb}(t) = \frac{10^{-10}}{\rho_w A_{oc}}\left(71.5T_{1980-1999}(t) + 20.4T^2_{1980-1999}(t) + 2.8T^3_{1980-1999}(t)\right), \tag{5}$$

where the factor 10^{-10} is used to convert GT to kg and m to cm, $\rho_w = 1 \times 10^3\,\mathrm{kg\,m^{-3}}$ is the water density and $A_{oc} = 3.6704 \times 10^{14}\,\mathrm{m}^2$ is the ocean surface area. This equation is then integrated in time:

$$X_{Gsmb}(t) = x^0_{Gsmb} + UL\int_{2006}^{t} \dot{X}_{Gsmb}(t')dt' \quad (6)$$

where x^0_{Gsmb} is the observed contribution between 1996 and 2005. To represent the difference between regional models, an additional uncertainty is added as L a random variable sampled from the log-normal distribution $\mathrm{e}^{\mathcal{N}(0,0.4^2)}$. A positive feedback between SMB and surface topography is also added. As the ice sheet loses mass its altitude decreases and the temperature at its surface increases, leading to increased melt. This is included with U that is a random variable following the uniform probability distribution between 1 and 1.15.

3.1.5 Antarctic Ice Sheet surface mass balance

The change in Antarctic ice sheet SMB was assumed to be due solely to an increase in accumulation, e.g. possible increase in runoff is neglected. This was estimated using the results of *Gregory and Huybrechts* [2006] from CMIP3 AOGCMs. Accumulation was taken to increase at 5.1 ± 1.5 % per degree of warming in Antarctica. The ratio of warming in Antarctica compared to GMST was taken to be 1.1 ± 0.2. The Antarctic SMB contribution to sea level is then computed as:

$$X_{Asmb}(t) = -x^{ref}_{Asmb} N_3 N_4 T_{1986-2005}(t), \quad (7)$$

with x^{ref}_{Asmb} the accumulation during the reference period taken to be $1923\,\mathrm{Gt\,yr^{-1}}$, N_3 and N_4 uncertainties following respectively $\mathcal{N}(5.1, 1.5^2)$ and $\mathcal{N}(1.1, 0.2^2)$. A minus sign is added because this accumulation of water on Antarctica brings sea level down.

3.1.6 Ice Sheet dynamics

Based on an expert assessment of the literature the range of the Greenland ice sheet dynamical processes contribution for 2100 is 1.4 to 6.3 cm for all scenarios, except RCP8.5 for which it is 2 to 8.5 cm. The mass loss rate at the beginning of the projection is taken as half of the observed rate from 2005 to 2010 (half of $0.46-0.80\,\mathrm{mm\,yr^{-1}}$), the other half being accounted for in the surface mass balance. A maximum (minimum) time series is then built starting in 2006 from the maximum (minimum) estimate of recent mass loss and ending in 2100 at the maximum (minimum) of the range for 2100 and assuming second order in time. These maximum and minimum time series are called x^{max}_{Gdyn} and x^{min}_{Gdyn} respectively. An additional 0.15 cm is added for the contribution before 2006 (x^0_{Gdyn}). The distribution is then taken as uniform between the maximum and minimum time series as follows:

$$X_{Gdyn}(t) = x^0_{Gdyn} + \left[U_2 x^{max}_{Gdyn}(t) + (1 - U_2)\, x^{min}_{Gdyn}(t)\right] \quad (8)$$

where U_2 follows a uniform probability distribution between 0 and 1.

The contribution from Antarctic dynamics is computed in the same way with starting contribution of 0.21-0.61 mm.yr^{-1} reaching -2 to 18.5 cm in 2100. It is independent of the scenario.

3.1.7 Land water changes

This term is based on projections of future dam constructions and depletion of ground water from human activities. The 5 to 95% quantiles for 2100 are -1 and 9 cm [*Wada* *et al.*, 2012]. The time evolution is done with a second order polynomial starting from present observed rate estimates of (0.26,0.49) [mm/yr] (5-95% range). A lower (upper) time series is constructed that start at the lower (upper) initial rate and end at the lower (upper) final estimate. These time series are called x_{grw}^{lower} and x_{grw}^{upper}. A central estimate (X_{grw}^{cen}) is obtained as the mean of the two. The final distribution is then computed as:

$$X_{grw}(t) = x_{grw}^{cen}(t) + \sigma_{grw}(t)N_5 \tag{9}$$

where N_5 is sampled from $\mathcal{N}(0,1)$ and with

$$\sigma_{grw}(t) = \left(\frac{x_{grw}^{upper}(t) - x_{grw}^{lower}(t)}{\alpha_{95} - \alpha_{05}} \right) \tag{10}$$

and α_q is the quantile function for a normal distribution. The land water contribution is taken as independent of temperature and emission scenario.

3.1.8 Final combination of contributors

The contributors are combined using a Monte Carlo method. The sea level contributors are random variables but they are not directly sampled, they are constructed from other random variables. In particular many contributors are built using N_1, that represents the uncertainty in future GMST. This is the reason why in this model the dependence structure is mainly prognostic (the result of model calculations) and not an input. The total sea level is obtained as:

$$X_{total} = X_{st} + X_{gic} + X_{Gsmb} + X_{Gdyn} + X_{Asmb} + X_{Adyn} + X_{grw} \tag{11}$$

A probability density function can then be constructed from X_{total} for each time t. The sampling is continued until convergence with an accuracy of 1 cm of the 99.9th percentile of the total sea level distribution is reached. This is found to be around 5×10^5 samplings for all cases.

3.2 Probabilistic model

This model is build with three modifications to the AR5 process-based model.

3.2.1 Antarctic dynamics

The Antarctic dynamics is modelled using response functions from three ice sheet models that have a representation of ice shelves as described in *Levermann et al.* [2014]. This method allows us to propagate uncertainty from GMST to the Antarctic dynamics contribution to sea level (Fig. 1). It also has the advantage of modelling the dependence between Antarctic dynamics and other sea level contributors through GMST. We choose to use the response functions only from the three models that explicitly represent ice shelves. These are the Pennsylvania State University 3-D ice sheet model (PenState-3D, *Pollard and Deconto* [2012]), the Parallel Ice Sheet Model (PISM, *Winkelmann et al.* [2011]; *Martin et al.* [2011]) and the SImulation COde for POLythermal Ice Sheets (SICOPOLIS, *Greve et al.* [2011]). Noting the response functions R_i and the basal melt at the Antarctic margin Δb we have:

$$X_{Adyn}(t) = \int_{1950}^{t} \Delta b(\tau) R_i(t-\tau) d\tau. \tag{12}$$

and modelling Δb as a function GMST gives:

$$X_{Adyn}(t) = \int_{1950}^{t} U_3 \alpha_m T(\tau) R_i(t-\tau) d\tau, \tag{13}$$

where U_3 is a continuous random variable representing basal melt sensitivity and following a uniform distribution between 7 and 16 my^{-1}K^{-1} and α_m is a discrete random variable representing the scaling coefficient between GMST and subsurface ocean warming around the Antarctic ice shelves. α_m is selected randomly from one of 19 CMIP5 climate models (see numerical values in *Levermann et al.* [2014]). In the original paper *Levermann et al.* [2014] compares two approaches, with and without including a time delay between GMST and subsurface ocean temperature. For simplicity we chose to only present the case without time delay.

3.2.2 Uncertainty of the CMIP5 model ensemble

The standard deviation of GMST and thermal expansion are initially computed from the CMIP5 ensemble and multiplied by 1.64 as done by *Le Bars et al.* [2017] and similar to *Kopp et al.* [2014]. This is done by setting γ to 1.64 instead of 1 in equations 1 and 2. This step is to reflect the decision of the AR5 authors to give a *likely* probability (66% or more) to the 5th to 95th percentile range computed from the climate model ensemble.

3.2.3 Correlation between GMST and thermal expansion

The correlation between thermal expansion and GMST is re-evaluated using the CMIP5 database. Using 28 models for RCP4.5 and 30 models for RCP8.5 we correlate the temperature difference and the thermal expansion difference between the periods 2091-2100 and 1986-2006. We find a correlation of 0.2 (-0.1 to 0.6) and 0.4 (0 to 0.6) respectively for the RCP4.5 and RCP8.5 scenarios. With 5th to 95th percentiles between brackets. *Rasmussen et al.* [2018] found a similar result with a r^2 of 0.10, which is equivalent to a Pearson correlation coefficient of 0.3. This shows that the simple assumption of a correlation coefficient of 1 made in *Church et al.* [2013] can be refined. To understand the physical drivers of this correlation, we can start with the following approximation for the ocean heat uptake F:

$$F = \kappa T \tag{14}$$

where T is an anomaly in GMST and κ is the "ocean heat uptake efficiency" [*Gregory and Mitchell*, 1997; *Raper et al.*, 2002]. The thermal expansion can then be written as:

$$X_{st}(t) = \epsilon \int_{0}^{t} \kappa T dt' \tag{15}$$

where ϵ is the "expansion efficiency of heat" [*Russell et al.*, 2000]. It becomes clear that if κ and ϵ are the same for all climate models then a correlation of 1 between GMST and thermal expansion is obtained. However, this is not the case. κ was shown to depend on the ocean stratification, in particular in the southern ocean [*Kuhlbrodt and Gregory*, 2012] and on the strength and depth of the Atlantic Meridional Overturning Circulation [*Kostov et al.*, 2014]. ϵ was also shown to vary between climate models [*Kuhlbrodt and Gregory*, 2012] because the location where the heat is stored depends on the ocean circulation. This has an influence on sea level because of the non-linearity of the equation of state of sea water. The fact that κ and ϵ are related to dynamical ocean processes that depend on model physics more than on GMST reduces the correlation between GMST and thermal expansion.

Given the uncertainty in the correlation and the fact that we do not know of a physical mechanism that would explain why the correlation is larger for RCP8.5 than for RCP4.5

we chose to use the central value of 0.3 for both scenarios. This is implemented in the model by replacing the random variable N_1 in equation 2 by N_{1low} defined as:

$$N_{1low} = \rho N_1 + N_I \sqrt{1 - \rho^2}, \tag{16}$$

where N_I is an independent random variable with distribution $\mathcal{N}(0, 1)$ and ρ is the desired Pearson correlation coefficient between N_{1low} and N_1. Since we focus on Spearman correlation we first convert the target Spearman correlation ρ_r using:

$$\rho = 2 \sin \frac{\pi}{6} \rho_r. \tag{17}$$

This relation is valid when computing the correlation between two random variable with a joint normal distribution [*Kurowicka and Cooke*, 2006].

3.2.4 Sensitivity experiments

Using this probabilistic model we assess the importance of choices made for the cross-correlation between sea level contributors by defining a low and a high estimate of dependence. The low estimate has a reduced correlation between GMST and thermal expansion (0 instead of 0.3) while other dependence relations do not change. For the high estimate, we choose a correlation of 0.6 between GMST and thermal expansion. Additional dependences are also introduced by, on the one hand, correlating the modelling uncertainty for Greenland SMB, Antarctic SMB and Glaciers and Ice Caps. This is implemented in the model by having a correlation of 1 between N_2 (equation 4), L (equation 6) and N_3 (equation 7). On the other hand we also include a correlation between the modelling uncertainty of Antarctic and Greenland dynamics by having a correlation of 1 between U_2 (equation 8) and R_i (equation 13). The rational for these additional dependences is that the numerical models used for these different areas are not independent because they are based on the same knowledge and that physical processes relevant for SMB or ice dynamics in these different regions are mostly the same. A summary table of some of the sensitivity experiments is given in table 2 and a visual summary of these links is shown in Fig. 1.

For simulations that do not use the independent assumption there is no simple way to relate the uncertainty in individual contributors and the uncertainty in total sea level. To assess the impact of individual contributors on the total uncertainty the full sea level model needs to be run again. For example to assess the contribution of thermal expansion to the total uncertainty equation 11 is replaced by:

$$X_{total,E(X_{st})} = E(X_{st}) + X_{gic} + X_{Gsmb} + X_{Gdyn} + X_{Asmb} + X_{Adyn} + X_{grw}. \tag{18}$$

Where E is the expected value operator. Then using the difference between X_{total} and $X_{total,E(X_{st})}$ the influence of the uncertainty of thermal expansion can be quantified. This is performed for each of the main contributors.

4 Results

Using the two models described above sea level projections are made for two climate scenarios RCP4.5 and RCP8.5 [*van Vuuren et al.*, 2011].

4.1 The IPCC AR5 process-based projections

The computations of the IPCC AR5 global process-based method are reproduced (see "partial" columns in table 3). We focus on the 5-95th percentiles range of these distributions because they were used by *Church et al.* [2013] to define the *likely* range (probability of 66% or more) that was broadly communicated. The results that we obtain are

	IPCC AR5	Probabilistic		
Parameters	Partial	Partial	Low dependence	High dependence
Scaling of model uncertainty (γ)	1	1.64	1.64	1.64
Correlation between GMST and thermal expansion	1	0.3	0	0.6
Correlation between SMB model uncertainty variables: N_2, L, M_3	0	0	0	1
Correlation between ice sheet dynamics model uncertainty variables: U_2, R_i	0	0	0	1
Contribution from Antarctic dynamics	IPCC AR5	LV14	LV14	LV14

Table 2. Summary of differences between the main simulations. LV14 is *Levermann et al.* [2014]

very close to the ranges reported by *Church et al.* [2013] that were 36-71 cm and 52-98 cm in 2100 respectively for RCP4.5 and RCP8.5.

The correlations between GMST and each sea level contributor is computed for each year of the projections and is shown in Fig. 2 for the RCP4.5 scenario. Contributors that are assumed independent of GMST were not included in the figure, for these processes the correlation is constant equal to 0. Thermal expansion is assumed to be completely correlated to GMST so the correlation is 1 and does not change over time. Other processes have some temperature dependence but also other sources of uncertainty, as a result the correlation with GMST is less than 1. For Antarctic SMB the correlation is negative because the increase in snow accumulation is likely to be larger than the increase in surface runoff as Antarctica warms up [*Gregory and Huybrechts*, 2006]. For all processes that depend on GMST, the correlation changes over time. The uncertainty for all of these processes depends both on mean temperature and on temperature uncertainty. An increase in the temperature uncertainty leads to increase the correlation with the GMST but an increase in the mean temperature only leads to increase the uncertainty of the process itself which reduces the correlation with GMST. This point is discussed in more details in the discussion section.

Since GMST is not a direct contributor to sea level the correlations with GMST do not have a direct impact on the uncertainty of sea level projections. However it does have an indirect impact on the correlations between sea level contributors. Since this method to project sea level uses 7 sea level contributors, there are a total of 21 (combination of $\binom{7}{2}$) correlations influencing the total sea level distribution. These are shown in table 4 for year 2100. We focus on the time evolution of the correlation of Glaciers and Ice Caps with other sea level contributors (Fig. 2). As a result of decreasing correlation with GMST over time the correlation between sea level contributors also decreases over time.

To assess the impact of these dependencies on the uncertainty of total global mean sea level we compare the partial correlation structure described above with two extreme sensitivity experiments. One assuming independence between contributors and the other one assuming a complete dependence with a correlation of 1 between all contributors. Results are shown for year 2100 in table 3. We see that the 5-95th percentile ranges are sensitive to the choices of correlation between sea level contributors. The independent case gives narrower 5-95th percentile ranges while the fully dependent case gives ranges that are a lot broader. The RCP8.5 scenario is more sensitive to the dependence choices than the RCP4.5 because temperature uncertainties are larger. Also the independent assumption is a lot closer to the partial correlation used in [*Church et al.*, 2013] than the

	RCP4.5			RCP8.5		
Percentiles	Partial	Independent	Dependent	Partial	Independent	Dependent
5.0	36	38	19	53	56	31
50.0	52	53	52	73	73	73
95.0	70	67	88	97	93	121

Table 3. Global mean sea level results from the IPCC AR5 global sea level model ("partial" correlation) and computed from the same individual contributions but with two extreme choices of correlation structure: "independent" and "dependent" with respectively correlation 0 and 1 between all contributors. Percentiles are in centimetres for the year 2100 compared to the reference period 1986-2005. Results are shown for two climate scenarios: RCP4.5 and RCP8.5.

fully dependent case. These results underline the importance of the choice of the correlation structure between sea level contributors when making projections even for the *likely* range.

4.2 A probabilistic projection

We explore here a probabilistic model in which the Antarctic dynamics is computed from the method described in *Levermann et al.* [2014]. With this method, since the standard deviation of GMST and thermal expansion are already multiplied by 1.64, the *likely* range is not given by the 5th to 95th percentiles but directly by the 17th to 83rd percentiles. The distribution of future Antarctic dynamic contribution to sea level has a slightly wider *likely* range and the median shifts towards higher values compared to *Church et al.* [2013]. Most importantly for the focus of this work, this method automatically creates a dependence between the Antarctic ice sheet dynamics contribution to sea level rise and GMST. This was discussed by *Le Bars et al.* [2017] but using a different method. The new dependency graph is shown in Fig. 1, all the correlations are shown in table 4 and the total global sea level percentiles are shown in table 5.

In this model the evolution of the correlations over time is similar to the AR5 process-based model. However, the magnitude of reduction over time is smaller for all processes except for Antarctic dynamics (Fig. 2). This is because in this model the standard deviation of GMST is multiplied by 1.64. This changes the relative importance of the increase ensemble mean GMST and the increase standard deviation. It matters because it is the relative importance of these two factors that influences the correlation (see discussion). Also the correlation between Antarctic dynamics and GMST is a lot larger in this probabilistic model than in the AR5 model. This was expected because in the AR5 model the connection was only through increased Antarctic SMB that lead to small increased Antarctic mass loss due to calving [*Church et al.*, 2013].

There is a difference between the partial correlation case and the independent and dependent cases (table 5). The expected value of the total sea level is the sum of the expected value of the contributors, it is independent of the dependence strength between contributors [*Beaumont*, 2005]. Therefore since the median in these distributions is not very far from the expected value we see that dependency has little impact around the median but it becomes larger further away from the median. For example the 99th percentile is reduced by 7 cm in the independent case and increased by 39 cm in the fully dependent case compared to the partial case for the RCP4.5 scenario.

IPCC AR5 Partial correlation								
	GMST	TE	GIC	GSMB	ASMB	Land Water	AD	GD
GMST	1.00	1.00	0.68	0.66	-0.59	0.00	0.02	-0.00
TE	-	1.00	0.68	0.66	-0.59	0.00	0.02	-0.00
GIC	-	-	1.00	0.45	-0.41	0.00	0.02	-0.00
GSMB	-	-	-	1.00	-0.40	0.00	0.02	-0.00
ASMB	-	-	-	-	1.00	-0.00	-0.04	0.00
Land Water	-	-	-	-	-	1.00	0.00	-0.00
AD	-	-	-	-	-	-	1.00	-0.00
GD	-	-	-	-	-	-	-	1.00

Probabilistic Partial correlation								
	GMST	TE	GIC	GSMB	ASMB	Land Water	AD	GD
GMST	1.00	0.30	0.83	0.82	-0.77	-0.00	0.46	0.00
TE	-	1.00	0.25	0.25	-0.23	-0.00	0.14	0.00
GIC	-	-	1.00	0.69	-0.65	-0.00	0.39	0.00
GSMB	-	-	-	1.00	-0.64	-0.00	0.39	0.00
ASMB	-	-	-	-	1.00	0.00	-0.37	-0.00
Land Water	-	-	-	-	-	1.00	-0.00	0.00
AD	-	-	-	-	-	-	1.00	0.00
GD	-	-	-	-	-	-	-	1.00

Probabilistic Low correlation								
	GMST	TE	GIC	GSMB	ASMB	Land Water	AD	GD
GMST	1.00	0.00	0.83	0.82	-0.77	-0.00	0.46	-0.00
TE	-	1.00	0.00	0.00	-0.00	0.00	0.00	0.00
GIC	-	-	1.00	0.69	-0.65	-0.00	0.39	-0.00
GSMB	-	-	-	1.00	-0.64	-0.00	0.39	0.00
ASMB	-	-	-	-	1.00	0.00	-0.37	-0.00
Land Water	-	-	-	-	-	1.00	-0.00	0.00
AD	-	-	-	-	-	-	1.00	-0.00
GD	-	-	-	-	-	-	-	1.00

Probabilistic High correlation								
	GMST	TE	GIC	GSMB	ASMB	Land Water	AD	GD
GMST	1.00	0.60	0.83	0.82	-0.77	-0.00	0.46	0.00
TE	-	1.00	0.50	0.50	-0.47	0.00	0.29	-0.00
GIC	-	-	1.00	1.00	-0.94	-0.00	0.40	-0.00
GSMB	-	-	-	1.00	-0.94	-0.00	0.39	-0.00
ASMB	-	-	-	-	1.00	0.00	-0.37	0.00
Land Water	-	-	-	-	-	1.00	-0.00	-0.00
AD	-	-	-	-	-	-	1.00	0.46
GD	-	-	-	-	-	-	-	1.00

Table 4. Correlation matrix of different simulations in year 2100 for the "partial" correlation case under an RCP4.5 scenario. The matrices are symmetric so the terms below the main diagonal are omitted. Acronyms are: Global Mean Surface Temperature (GMST), Thermal Expansion (TE), Greenland Surface Mass Balance (GSMB), Antarctic Surface Mass Balance (ASMB), Antarctic Dynamics (AD) and Greenland Dynamics (GD).

RCP4.5					
Percentiles	Partial	Low dependence	High dependence	Independent	Dependent
5.0	34	36	32	38	15
10.0	38	39	37	41	22
17.0	42	43	41	44	30
50.0	55	55	54	55	53
83.0	70	69	71	68	82
90.0	76	75	78	73	94
95.0	85	83	87	80	108
99.0	105	103	108	98	144
99.9	139	138	145	132	203
RCP8.5					
Percentiles	Partial	Low dependence	High dependence	Independent	Dependent
5.0	51	53	48	56	25
10.0	56	58	54	61	35
17.0	62	63	60	65	45
50.0	79	79	79	80	77
83.0	101	99	102	97	117
90.0	110	108	112	105	134
95.0	121	119	125	114	154
99.0	150	146	154	139	206
99.9	195	190	199	178	288

Table 5. Global mean sea level results from the probabilistic model. "Partial correlation" is the reference case, "low dependence" and "high dependence" are sensitivity experiments using high and low values of some parameters defining the dependence structure. Two extreme choices of correlation structure are also shown "independent" and "dependent" with correlation 1 between all contributors. Percentiles are in centimetres for the year 2100 compared to the reference period 1986-2005. Results are shown for two climate scenarios: RCP4.5 and RCP8.5

4.3 Uncertainty in the dependence between contributors for a probabilistic projection

We now turn to the problem of the uncertainty in assessing the strength of dependence between sea level contributors. We address this problem by designing two additional sensitivity experiments. One in which the dependency is reduced and another one where it is increased compared to the partial case. We use different possible links between sea level contributors instead of only GMST (Fig. 1, section 3.2.4). We consider these two cases as the upper and lower end of a reasonable range of correlation strength. The uncertainty in dependence is then defined as the difference between the high and the low dependence cases. This uncertainty is compared with the uncertainty due to the main sea level contributors. To measure the importance of the uncertainty of individual sea level contributors we recompute the total sea level replacing one contributor by its expected value (see equation 18). The difference between the total sea level with and without including this contributor's uncertainty gives a measure of its contribution to the total sea level uncertainty [*Saltelli et al.*, 2008]. These results are shown for RCP4.5 and RCP8.5 in year 2100 in Fig. 3a and c where positive (negative) values mean that a contributor leads to increase (decrease) that particular quantile. All contributors tend to increase the uncertainty of total sea level. This effect can be seen from the positive (negative) values of percentiles higher (lower) than 50. Antarctica (SMB and dynamics) provides the largest uncertainty in 2100 for both scenarios. The larger impact of Antarctica on the high percentiles compared to the low percentiles is also seen in Fig. 3a and c. This is because of the positive skewness of Antarctic uncertainty in this model. The same asymmetry can be seen for Greenland for the RCP8.5 scenario. After Antarctica the main contributors to the total uncertainty are glaciers and ice caps for RCP4.5 and Greenland for RCP8.5.

We can also look at the variations in time of the relative importance of these contributors for a given range of probability, for example the *very likely* range (5st to 95st percentile in this probabilistic model, Fig.3b,d). The growth of the uncertainty contribution is close to linear for most contributors except for Greenland and Antarctica for which the growth accelerates over time. As a result the relative importance of some contributors changes over time. In particular for RCP8.5 Greenland contribution to the uncertainty is the smallest up to around 2070 but becomes the second largest just after Antarctica from around 2090. The uncertainty arising from dependence assumption (red curve) has a similar evolution as the thermal expansion uncertainty for both scenarios, with a little faster growth over time. At the end of the century its magnitude (around 7 and 10 cm for RCP4.5 and RCP8.5) is similar to that of thermal expansion, Greenland ice sheet (SMB and dynamics) and glaciers and ice caps.

5 Discussion

Results show that when the uncertainty in temperature is increased (e.g. γ is increased in equation 1) the correlation between processes increases. However the absolute value of the correlation between sea level contributors and temperature generally decreases over time even though the uncertainty in temperature increases. We hypothesised that this is the result of a competition between increase mean temperature that decreases the correlation and increase uncertainty that increases the correlation. To illustrate this hypothesis, let's take a simple example of a contributor to sea level (X) that is related to the GMST in the following way:

$$X = (\mu_0 + \sigma_0 N_0)\, T \tag{19}$$

where μ_0 and σ_0 are constants and N_0 is a random variable following $\mathcal{N}(0, 1)$. For this example the Pearson correlation between X and T has an analytical expression that stays relatively simple:

$$\rho_{X,T} = \frac{E(N_1^2)}{\sqrt{\frac{\sigma_0^2 \overline{\mathbf{T}}^2}{\sigma(\mathbf{T})^2 \mu_0^2} + 1 + \frac{\sigma_0^2}{\mu_0^2} E(N_0^2 N_1^2)}} \tag{20}$$

It is now clear from equation 20 that $\rho_{X,T}$ decreases when $\overline{T}$ increases and increases when $\sigma(T)$ increases. The behaviour is similar for the Spearman correlation but the analytical computation is less simple so we do not include this here. The relation between the evolution of mean and uncertainty of GMST depends on time and on climate scenarios [*Jackson et al.*, 2018]. For the RCP2.6 scenario the uncertainty increases more than the mean temperature during the 21st century [*Jackson et al.*, 2018] so a decrease of the correlation over time might not occur contrary to what we see here for RCP4.5 and RCP8.5.

The uncertainty in the dependence parameters could be included in the sea level projection model. This means that the parameters that we used to define sensitivity experiments (correlation between GMST and thermal expansion, correlation between SMB and ice dynamics uncertainty) could also be sampled randomly from predefined distributions during the Monte Carlo simulation. This would increase the computational cost of the model because convergence would slow down, but it would make the model more consistent.

Up to now, all probabilistic sea level projections are still conditional on future greenhouse gas concentration pathways. Therefore, the uncertainty provided do not include greenhouse gas emissions uncertainty nor carbon cycle uncertainty. For a fully probabilistic model that would propagate uncertainty all the way from emissions to sea level the issue of dependence between contributors would be even more important. This is because in such a model the GMST uncertainty would be larger and as a result the dependence between sea level contributors would increase.

The Antarctic contribution that we use here do not include the hydrofracturing of Antarctic ice shelves nor the structural collapse of tall ice cliffs [*Levermann et al.*, 2014]. These mechanisms were shown to increase the sensitivity of Antarctic mass loss to emission scenarios because of the key role of surface melting at the surface of ice shelves [*Pollard et al.*, 2015; *Deconto and Pollard*, 2016]. Models that include these processes increases the dependence between contributors and total sea level uncertainty [*Le Bars et al.*, 2017; *Kopp et al.*, 2017].

In this paper, relatively little attention is paid to Greenland dynamics because its expected future contribution and uncertainty is relatively small [*Nick et al.*, 2013]. We follow the decision of *Church et al.* [2013] to assume independence between GMST and Greenland dynamics. This is a simplifying assumption that is not consistent with the fact that in *Church et al.* [2013] (and in our models) Greenland dynamics contribution is higher for RCP8.5 compared to the other scenarios. To make the sea level projection model more consistent, this assumption could be relaxed either using a study similar to *Levermann et al.* [2014] but for Greenland or using a simple linear relationship as was done by [*Le Bars et al.*, 2017] for Antarctica. In any case, we expect that this relation would have a small impact on the resulting total uncertainty in sea level projections.

Only global sea level projections were discussed in this paper. Implementing dependence in regional projections is straightforward for ice sheets and glaciers because the dependence to GMST does not change, only fingerprints will modulate their relative contributions. When an ice sheet or a glacier loses mass, sea level drops in its vicinity. This leads to a reduction of the uncertainty close to the location of mass loss due to an anti-correlation between contributors. Also new processes become important regionally like local steric effects, changes of wind forcing and in ocean currents. These processes are modelled by global climate models so the correlations between these effects and GMST can be analysed using the CMIP databases.

Sometimes, for practical applications, mean sea level probabilistic projections are not used on their own but together with other processes like inter-annual variability of sea level, tides, storm surges, wave setup, river discharge and rain to investigate extreme events at coastal locations [*Le Cozannet et al.*, 2015; *Vousdoukas et al.*, 2017]. Developing models of dependence between these processes will improve the quantification of the frequency of future flooding events [*Little et al.*, 2015].

6 Conclusion

We have shown that the dependence between sea level contributors has an impact on the uncertainty of sea level projections. A way to model some dependence is to include a correlation between sea level contributors and GMST [*Church et al.*, 2013]. The sea level projection from this approach were shown to have higher uncertainty than assuming independence and less than assuming complete dependence. These two choices of independence and perfect correlation should be viewed as extremes, that can give insightful lower and upper bound of the uncertainty. The dependence choices were shown to be more important for high greenhouse gas emission scenario and for high percentiles. The correlation between sea level contributors was also shown to changes over time. We discussed the fact that this is the result of a competition between expected value and uncertainty of GMST. The former decreases the correlations while the later increases them.

Unfortunately the dependence between contributors are loosely constrained because they cannot be observed. This leads to an additional uncertainty similar in magnitude to the uncertainty due to thermal expansion and Greenland mass loss. Therefore it might be relevant to take this uncertainty into account for applications that require accurate uncertainty quantification.

A direct consequence of this work concerns the quantification of future risks of sea level. We showed that the often used independence assumption is not a neutral choice. It underestimates the uncertainty and as a result users of these projections are underestimating the risks of high-end and low-end sea level rise [*Hinkel et al.*, 2015]. Understanding the importance of the dependence between sea level contributors also helps understanding the difference between different high-end scenarios, for example [*Katsman et al.*, 2011] assumed independence and reached a much lower high-end projection than [*Jevrejeva et al.*, 2014] who assumed perfect correlation. Our model shows that for the RCP8.5 scenario the difference of 99th percentile in 2100 between these two extreme assumptions is 67 cm, which shows the importance of this choice.

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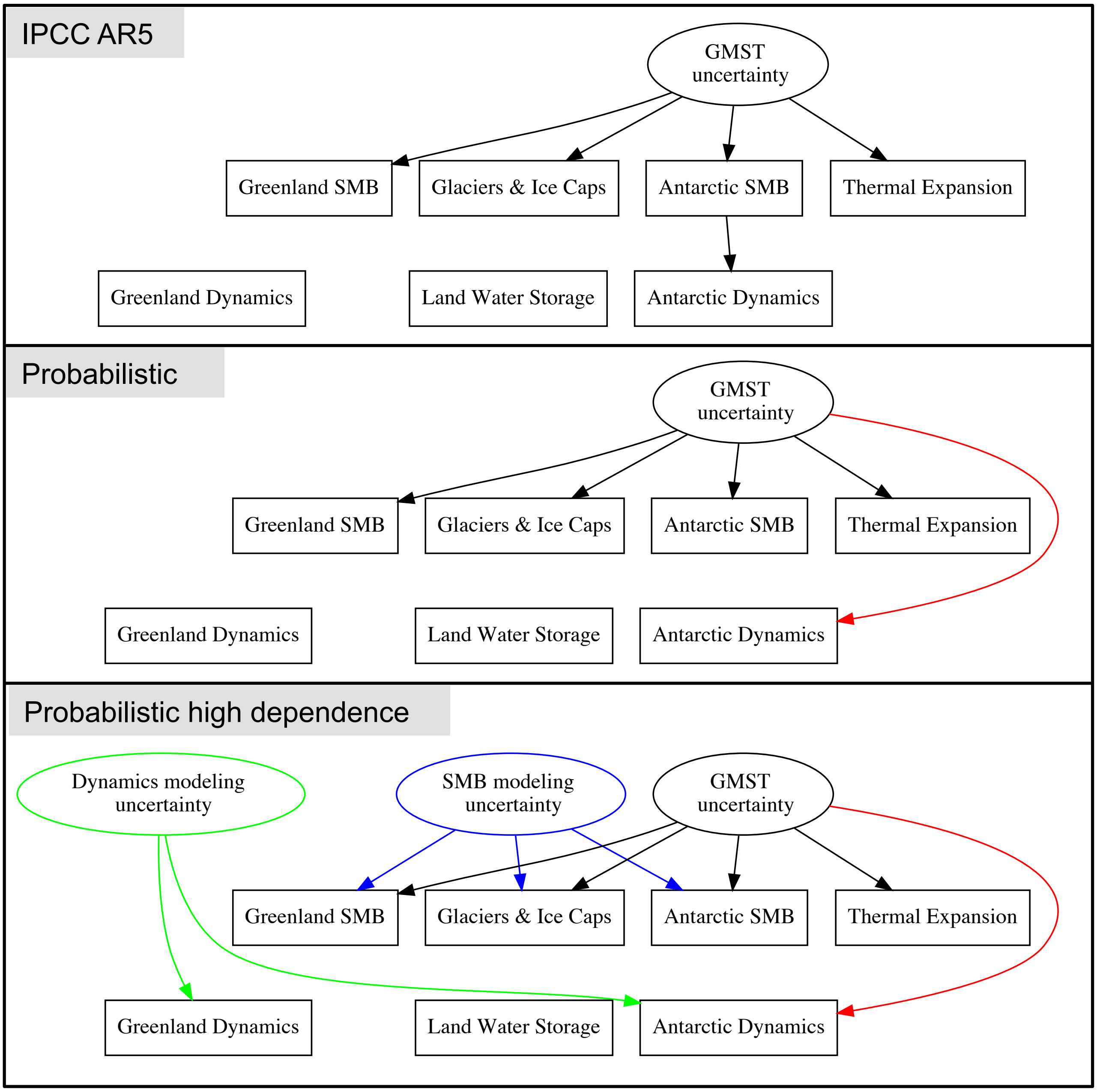
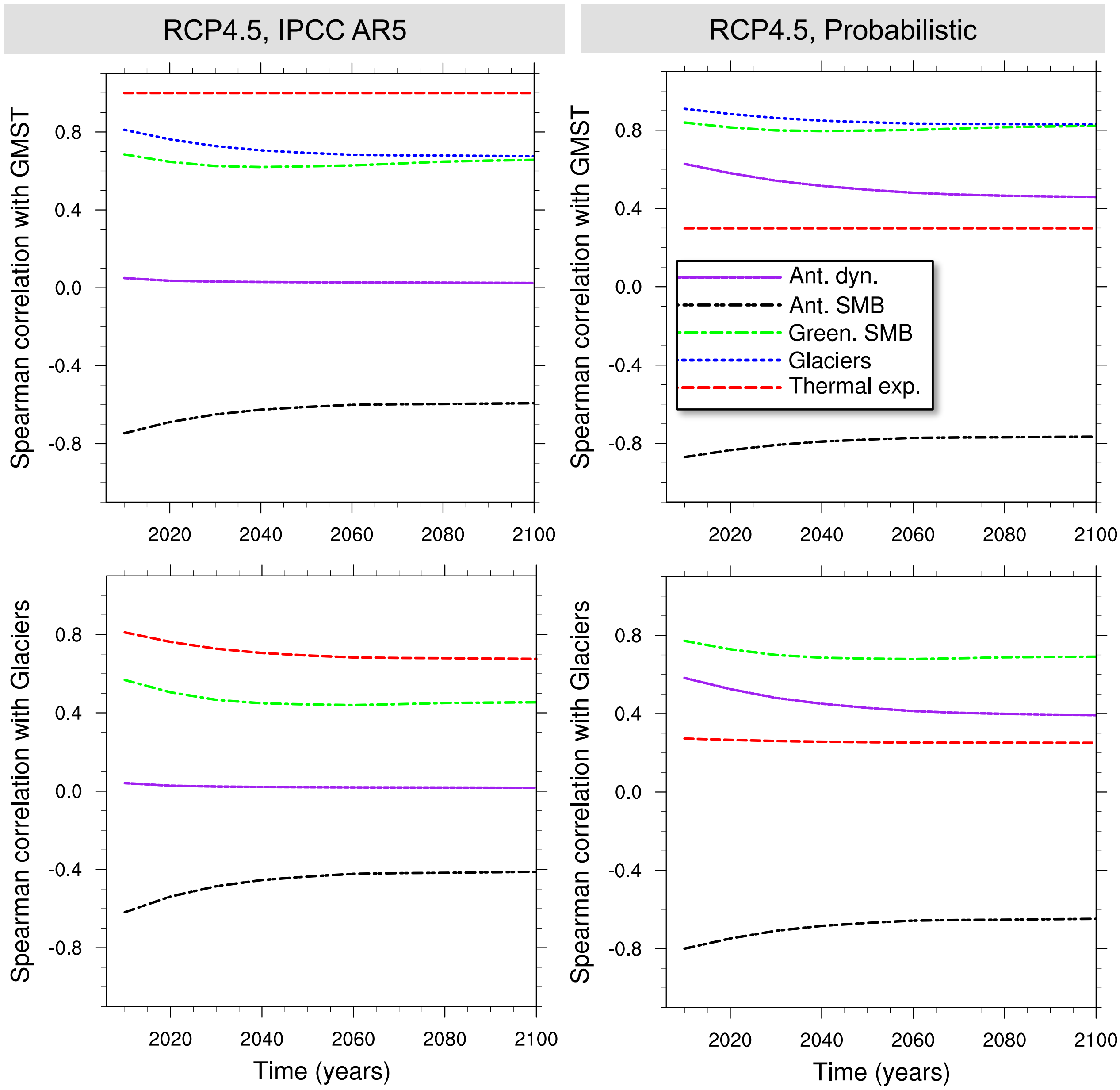


Figure 1. Dependency graph for different sea level projections. Sea level contributors are represented in rectangular boxes while factors providing an external influence are represented in oval shapes. Arrows represent direct dependence relationship. The indirect dependences are not represented here.



443 **Figure 2.** Time evolution of Spearman correlation for the IPCC AR5 model (left column) and
444 the probabilistic model (right column), for the RCP4.5 scenario.

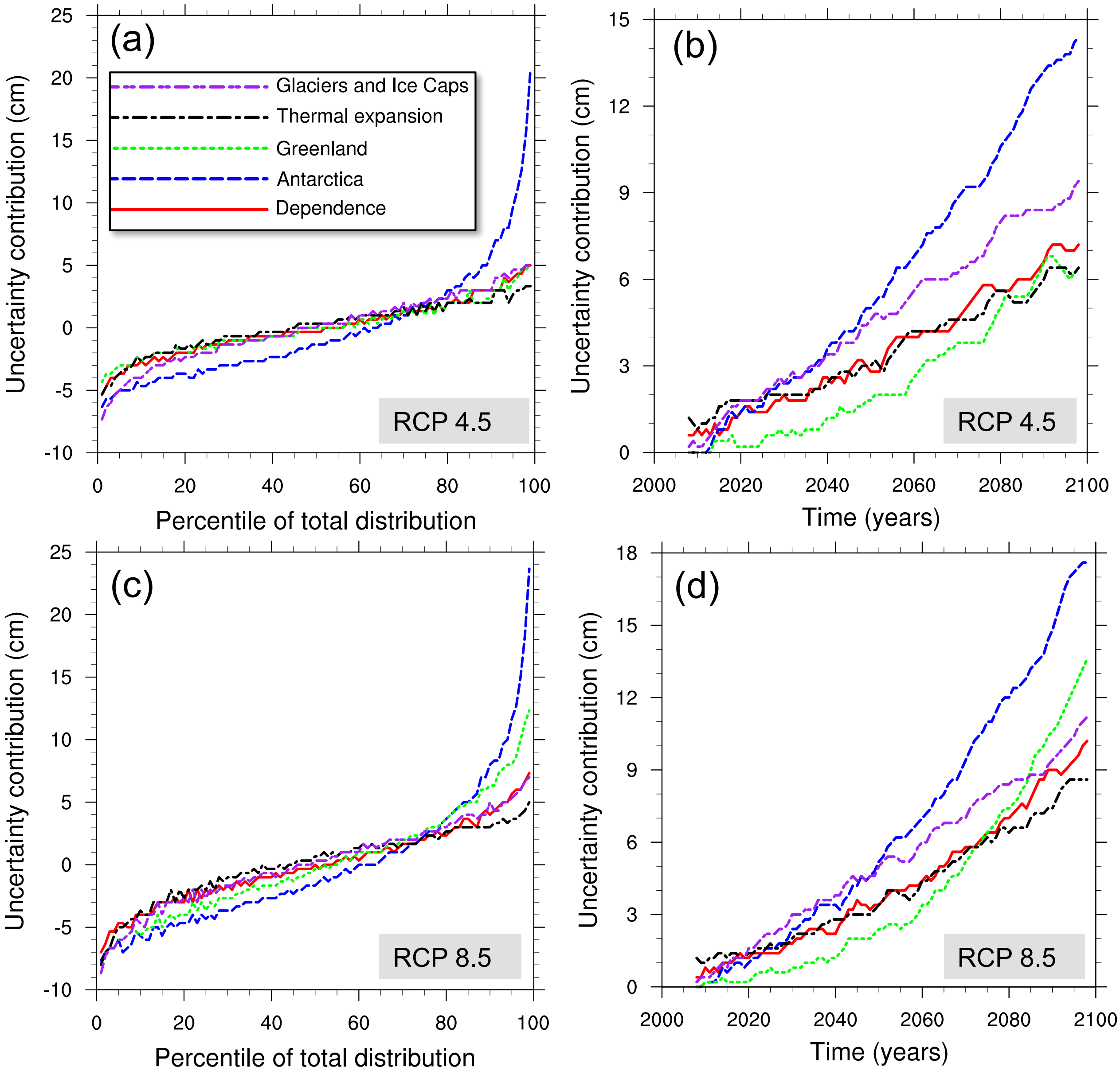


Figure 3. (a) Uncertainty of total sea level in 2100 due to the uncertainty of the main sea level contributors compared to that due to the dependence between them. Result is shown for each percentile. For Greenland and Antarctica SMB and dynamics are added together. (b) Time series of the increase of the *very likely* range (5th to 95th percentile) of total sea level due to the uncertainty of each contributor and due to the dependence between them. Panels (c) and (d) are the same as (a) and (b) for scenario RCP8.5.